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Computational Model for Reward-Based Generation and Maintenance of Motivation

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Abstract. In this paper, a computational model for the motivation process is presented that takes into account the reward pathway for motivation generation and associative learning for maintaining motivation through Hebbian learning approach. The reward prediction error is used to keep motivation maintained. These aspects are backed by recent neuroscientific models and literature. Simulation experiments have been performed by creating scenarios for student learning through rewards and controlling their motivation through regulation. Mathematical analysis is provided to verify the dynamic properties of the model.

Keywords: Motivation · Cognitive modelling · Reward-based learning

1 Introduction

Motivation is an important internal process for any human to achieve their targets and goals. Motivation is a complex topic which is usually mixed with desire, value and goal, that's why there is no consensus on whether the motivation is a state or a process. A number of psychological theories on motivation exists for example learning theory, attribution theory, self-determination theory etc. [1, 2]. A motivation may be intrinsic or extrinsic or other. A motivation that leads to perform any behavior or activity for self-enjoyment is known as intrinsic motivation, whereas the extrinsic motivation, on the other hand, is to act for external rewards. For example, research student has extrinsic motivation to write, if they do so in the hope of getting published or being famous.

A reward is an environmental stimulus that pulls people to act in a particular way. it is extremely useful and mostly used force in any learning environment. Neuroscientific examinations of motivation have set up the framework which provides a way to design different models or systems. From the neuroscience knowledge, two constructs are so relevant for consulting psychology. Firstly, how much motivation is linked to the past and how reinforcement learning is used to learn and storing it in the memory [3]. For good reason, we evolved to be highly sensitive to learn where we receive rewards and to work hard to recreate the situations that brought them about. This reinforcement leaning is implemented in our model through the body loop. Reinforcement of new behavior is extremely difficult because it means working against this powerful well

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system. Thus usually, it is grounded in the neuroscience of motivation and reinforcement learning is to start behavior change with modest rewards [2].

Moreover, to maintain motivation continues learning and memory is required. Dopamine neuro transmitter plays an important role in learning, memory and habit formation [4]. According to reinforcement theory magnitude of leaning depends on the dopamine release. To release a proper amount of dopamine, the reward frequency and time should be maintained. Otherwise repeated use of reward increase expectation will decrease the learning rate or make it static at the end. In proposed model control state is used to check for continues use of reward for certain action, which gets activated if the reward is always repeated which cause the motivation down and the agent start moving to next action. To maintain motivation it is usually suggested to give a surprising reward with cognitive gap [1].

The paper is structured as follows. Section 2 consists of detail discussion about all the neurological background for reward pathway and reward prediction error. Section 3 presents the model and the temporal causal network modelling approach. In Sect. 4 the simulation of the scenario of the computational model is discussed. Section 5 consists of the mathematical analysis of some of the dynamic properties of the model. Finally, Sect. 6 contains the conclusion.

2 Background

2.1 Motivation Generation; Reward Pathway

The primary region of the brain that is associated with reward is the dopamine pathway and it is widely known as the reward pathway. Dopamine neuro transmitter is produced in a ventral tegmental area (VTA), passes through Globus Pallidus and releasees into the nucleus accumbens (NAcc) [5]. Dopamine pathway is divided into mesolimbic dopamine system and the mesocortical dopamine system. The mesolimbic is in charge of reward anticipation and learning. Whereas the mesocortical system includes, encoding the relative value of the reward and goal-directed behavior [1]. The main brain area that are involved in reward processing are VTA, NAcc, the amygdala, the hippocampus, ventromedial prefrontal cortex, adjacent medial orbitofrontal cortex (vmPFC/mOFC), lateral orbitofrontal cortex (IOFC), anterior cingulate cortex (ACC) and a lateral anterior prefrontal cortex (aPFC) [5]. All the species ae preprogrammed to approach primary rewards (food, sexual excitement etc.), but in case of secondary rewards like money, the OFC encodes and represents the associative value of reward and update the value for future decision making.

The reward system induce positive emotion that make the organism approach, or increase the frequency of target behavior. The choice of an action depends on reward mechanisms, as a form of valuing of the options [6]. Taking decision for action among the available options depend on the valuing process, every available reward option is coupled with an associated feeling related to valuation whether that option will provide satisfaction or not. For this mode among the available option one having strongest valuated feeling performs as a GO signal through the body loop and else are NO–GO options. The as-if body loop consists of [7]:

sensoryrepresentation → preparationforbodilychanges → feltemotionsensoryrepresentation → preparationforbodilychanges → feltemotion

2.2 Motivation Maintenance; Reward Prediction Error

As the stimulus-action-outcome is learned through the reinforcement and feeling, now the level of reward predication error (RPE) has to been balanced to maintain the motivation. From neuroscience prospective, dopamine plays a major role in motor performance conditioning learning and memory. Insufficient amount of dopamine causes stiffness and paralysis and excessive dopamine may result in behavioral disorders such as schizophrenia, impulse control disorder etc. [1]. The expectation about the reward makes an RPE unbalanced, positive RPE is generated when an outcome is better than expected reward or unexpected rewards are given, whereas negative RPE is generated when the outcome is worse than expected rewards or expected rewards are omitted [1]. The brain region involved in value signals are the amygdala, orbitofrontal cortex (OFC), ventromedial prefrontal cortex (vmPF), and ventral & dorsal striata and some others.

From Psychological prospect, repeated use of reward increase expectation which leads to reducing positive RPE, and reach to stable stage latter in time [1]. To maintain student motivation, a certain amount of dopamine should be release during the pursuit of target the behavior. The dopamine can be released by changing the type or frequency of reward.

A stimulus-action generates the associated feeling via recursive body and as-if body loops [7, 8], which can predict the consequences and satisfaction of particular option before taking action. This is done by evaluating the options using loops involving interaction between feeling and preparation. The connections from feeling to preparation can be either assumed static or adaptive. In this article we used adaptive connection strengths because here learning is involved which is usually a transfer from previous experiences [9].

3 Computational Model

In this section, the proposed computational model is discussed, based on the literature described in Sect. 2. The process starts with an external stimuli cause the agent to take some action to fulfil its goal. In relation to a goal (in our simulation it is learning Dutch language), particular actions are considered and the extent to which they will provide a feeling of satisfaction.

Furthermore, causal relationships in the model are based on the neurological literature presented in the Sect. 2; they do not take specific neurons into consideration but use more abstracted cognitive or mental states for the design of the model (through an interlevel relation between the neurological level and the cognitive/affective mental modelling level). An overview of the model is depicted in Fig. 1. The concepts used are explained in Table 1.

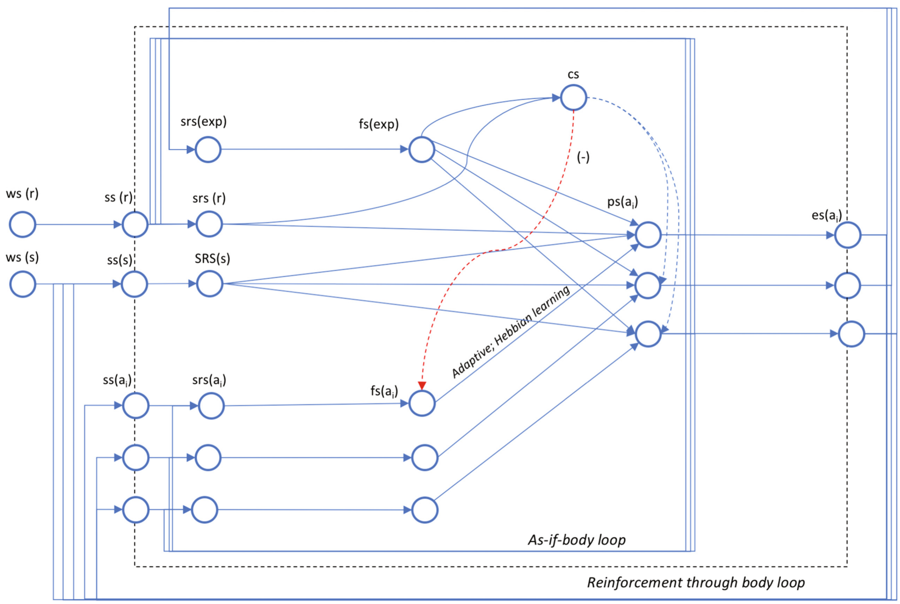

Fig. 1. Computational model for motivation through reward.

The temporal causal-network modelling approach [10, 11] has been used for modelling. The temporal dimension enables the modelling of cyclic causal relations with exact timing. In broader terms, there are some similarities between artificial neural networks and this approach, for example in the case of continuous time and recurrent, but there are important differences as well. For example, no hidden layer exists that do not represent any real-world phenomena; each state within this approach should be clearly defined with exact causal and temporal dimensions.

The models in temporal causal network modelling approach can be represented in two ways: conceptual representation and numerical representation. Both types of representation can be easily transformed into each other in a systematic manner.

Conceptual representation can be done through graphs or matrices. Whereas graphical representation involves states which represent some real world phenomena and the arrows show the causal relation between two states. Some additional information is given below:

- Value of connection (ωX, Y) representing strength of causality and it value ranges between [−1, 1].
- How fast a state Y can change upon casual impact. Speed factor is denoted by ηY, and value ranges between [0, 1].
- For multiple impacts on state Y, combination function $cY(\ldots)$ is used to combine the effect. There are a number of combination functions defined, varying from simple sum function to advance logistics function.

Table 1. The process and related states with description.

Process	Formal States name	Informal name	Description
Environment	ws(w)	World state	The world situation the person is facing, the stimulus, in the example w is a Dutch language book
	ss(w)	Stimulus State for World	The person senses the world through the sensor state
Motivation generation	srs(w)	Sensor representation state for World	Internal representation of sensory world information on w
	ss(r)	Sensory state of reward	Sensing reward through sensors
	srs(r)	Sensory representation of reward state.	Mental representation of reward
	ps(ai)	Preparation for i^{th} action	The human maintains an action/body representation srs(a) in the brain. Before performing an action, a feeling state FS(a) for action is generated by predictive as-if body loop
	fs(ai)	Feeling state of i^{th} action	
	es(ai)	Execution state of i^{th} action.	The execution of action change the situation and used to learn through body loop.
Maintenance of motivation	srs(exp)	Sensory representation state of expectation	The continues use of reward stop the learning process through the feeling sate FS(exp)
	fs(exp)	Feeling state of expectation	
	cs	Control state	Control state activated when expectation get higher using same reward

The conceptual representation of model can be translated into numerical representation as follow. For any state Y at any time point *t*, Y(t) denotes the activation value of Y. The causal impact of state X on Y at time point t, can be defined by:

$$\mathbf{Impact_{X,Y}} = \omega_{X,Y}X(t). \tag{1}$$

Total aggregated impact of the multiple impact on state Y at time *t* combined by combination function $cY(\ldots)$ can be defined by

$$\begin{aligned} \mathbf{aggimpact_Y(t)} &= c_Y\left(\text{impact}_{X1,Y},\ \text{impact}_{X2,Y},\ \text{impact}_{X3,Y},\ \cdots\right) \\ &= c_Y(\omega_{X1,Y}X_1(t), \omega_{X2,Y}X_2(t), \omega_{X3,Y}X_3(t),\ \ldots) \end{aligned} \tag{2}$$

the aggimpact$_Y$(t) will have upward or downward effect at time point *t*, but how fast this change takes place depends on the speed factor η_Y,

$$Y(t+\Delta t) = Y(t) + \eta Y\,[\text{aggimpact}_Y(t) - Y(t)]\,\Delta t \tag{3}$$

The following difference and differential equation can be obtained for state Y:

$$Y(t+\Delta t) = Y(t) + \eta Y\,[c_Y(\omega_{X1,Y}X_1(t), \omega_{X2,Y}X_2(t), \omega_{X3,Y}X_3(t), \ldots) - Y(t)]\Delta t \tag{4}$$

$$dY(t)/dt = \eta Y\,[cY(\omega_{X1,Y}X_1(t), \omega_{X2,Y}X_2(t), \omega_{X3,Y}X_3(t), \ldots) - Y(t)] \tag{5}$$

In the proposed model, the advanced logistic sum combination function alogistic$_{\sigma,\tau}$ (…) (Eq. 6) is used as the standard combination function for all state except ws(r) and ss(r) (Eq. 7), where simple identity function is used:

$$\begin{aligned} c_Y(V1, \ldots Vk) &= \text{alogistic}\sigma, \tau V1, \ldots, Vk) \\ &= (1/1 + e^{-\sigma(v_1 + \ldots + v_k - t)} - 1/1 + e^{\sigma,\tau}), t(1 + e^{-\sigma,\tau}) \end{aligned} \tag{6}$$

$$cY(V) = \text{id}(V) = V \tag{7}$$

The feeling state act as a measuring and valuating state, the association between good feeling about certain action can be learnt over time based on past experiences. For this a Hebbian learning mechanism has been used by which such connections may automatically emerge or strengthen. The connections from feeling fs(a_i) to preparation ps(a_i) with weights ωfs(a_i), ps(a_i) have been made adaptive [12, 13]. The numerical representation of Hebbian learning is [10]:

$$\begin{aligned} \omega_{fs(ai),ps(ai)}(t+\Delta t) &= \omega_{fs(ai),ps(ai)}(t) + [\eta\ fs_{ai}(t)ps_{ai}(t)(1 - \omega_{fs(ai),ps(ai)}(t)) \\ &\quad - \zeta\omega_{fs(ai),ps(ai)}(t)]\,\Delta t \end{aligned} \tag{8}$$

4 Simulation

A number of simulations have been performed to test the model using MATLAB environment. One of the scenario discussed in this paper is as follow

Consider an academic situation where a student Marvik intended to learn the Dutch language. Mavrick has three options, firstly, start reading a book, secondly use internet and lastly attend the classes. The process is complimented by the teacher through verbal praise (reward-driven approach) for first of his action. This reward leads Marvik to work hard to get the reward and eventually ends in leaning language. By reinforcement rule, he associated the target behavior with reward. But always having the same reward he gets demotivated and starts losing that behavior.

The following is a brief summary of the agent’s internal causality when given stimulus ‘s’ and reward ‘r’ as inputs

I. External stimulus ‘s’ and reward ‘r’ will occur and trigger preparation of action a_i.
II. Based on the preparation state for a_1, the sensory representation of the (positive) predicted effect of a_1 is generated.
III. The execution of a_1 increase the expectation for the reward ‘r’.
IV. The control state gets activated after some threshold when expectation gets high with the same reward.
V. To take negative prediction error into account, the activation of control state slow down the learning or even stop it.

The combination function, initial value and speed factor for each state are given in Table 2, whereas Table 3, defines the connection weights between states.

Table 2. The parameters for combination function (alogistic) for given model.

States	Parameters (σ,τ)	States	Parameters (σ,τ)
ws(s)	σ = 5, τ = 0.5	fs(exp)	σ = 6, τ = 0.7
ss(s)	σ = 5, τ = 0.5	ps(a1)	σ = 6, τ = 0.7
ss(a1)	σ = 5, τ = 0.6	ps(a2)	σ = 6, τ = 0.7
ss(a2)	σ = 5, τ = 0.6	Ps(a3)	σ = 6, τ = 0.7
ss(a3)	σ = 5, τ = 0.6	es(a1)	σ = 9, τ = 0.4
srs(r)	σ = 6, τ = 0.5	es(a2)	σ = 9, τ = 0.4
srs(s)	σ = 6, τ = 0.5	es(a3)	σ = 9, τ = 0.4
srs(a1)	σ = 6, τ = 0.6	fs(a1)	σ = 3, τ = 0.6
srs(a2)	σ = 6, τ = 0.6	fs(a2)	σ = 3, τ = 0.6
srs(a3)	σ = 6, τ = 0.6	fs(a3)	σ = 3, τ = 0.6
srs(exp)	σ = 6, τ = 0.7	cs	σ = 4, τ = 0.7

Table 3. Connection weights.

Connection	Weight	Connection	Weight	Connection	Weight
$\omega_{ws(r),ss(r)}$	1	$\omega_{srs(a1),fs(a1)}$	1	$\omega_{es(a1),ss(s)}$	1
$\omega_{ws(s),ss(s)}$	1	$\omega_{srs(a2),fs(a2)}$	1	$\omega_{es(a2),ss(s)}$	1
$\omega_{ss(r),srs(r)}$	1	$\omega_{srs(a3),fs(a3)}$	1	$\omega_{es(a3),ss(s)}$	1
$\omega_{srs(r),ps(a1)}$	1	$\omega_{fs(a1),ps(a1)}$	1	$\omega_{es(a1),srs(a1)}$	1
$\omega_{srs(r),ps(a2)}$	1	$\omega_{fs(a2),ps(a2)}$	1	$\omega_{es(a2),srs(a2)}$	1
$\omega_{srs(r),ps(a3)}$	1	$\omega_{fs(a3),ps(a3)}$	1	$\omega_{es(a3),srs(a3)}$	1
$\omega_{srs(exp),fs(exp)}$	1	$\omega_{ps(a1),es(a1)}$	0.3	$\omega_{es(a1),srs(exp)}$	1
$\omega_{ps(a1),srs(a1)}$	1	$\omega_{ps(a2),es(a2)}$	0.3	$\omega_{es(a2),srs(exp)}$	1
$\omega_{ps(a2),srs(a2)}$	0.4	$\omega_{ps(a3),es(a3)}$	0.3	$\omega_{es(a3),srs(exp)}$	1
$\omega_{ps(a3),srs(a3)}$	0.4	$\omega_{fs(exp),ps(a1)}$	1	$\omega_{fs(exp),cs}$	1
$\omega_{ps(a1),srs(r)}$	1	$\omega_{fs(exp),ps(a2)}$	1	$\omega_{srs(r),cs}$	1
$\omega_{ps(a2),srs(r)}$	1	$\omega_{fs(exp),ps(a3)}$	1	$\omega_{cs,fs(a1)}$	-0.4
$\omega_{ps(a3),srs(r)}$	1	$\omega_{cs,ps(a3)}$	0.4	$\omega_{cs,ps(a2)}$	0.4

In the scenario, the strength of the connection weights $\omega fs(a_{i)}$, $ps(a_i)$ from feeling to the considered preparation state, change over time through the hebbian learning mechanism. Initial values for all states have been chosen 0 except the world state ws (s) = 1 and ws(r) = 1, which depends on the scenario. The simulation is executed for some scenarios for 480 time points; the time step $\Delta t = 0.1$, learning rate $\eta = 0.2$ and extinction rate for all three states is $\zeta = 0.095$, when hebbian learning is used.

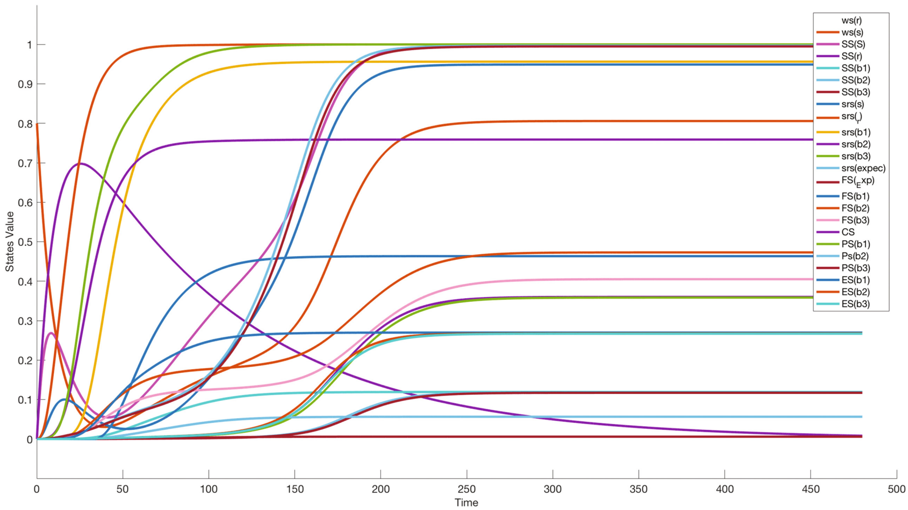

Fig. 2. The figure shows the overall execution of the model. Initially the **Preparation state** for action 1 is highly activated due to reward, then latter due to over expectation, control state gets activated and other action starts emerging.

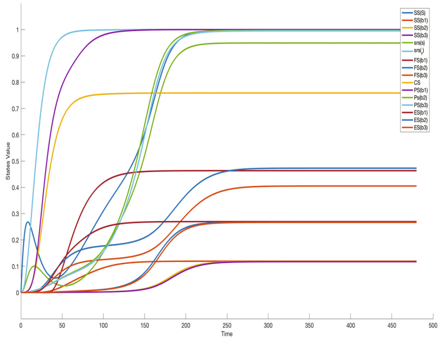

Fig. 3. The preparation and the feeling for action a_1 get higher.

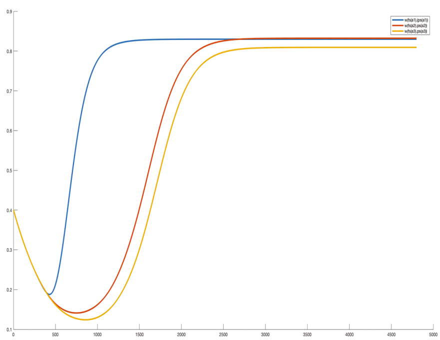

Fig. 4. The first action is learned earlier than other two.

In Fig. 2, an agent takes an action among the available options after the onset of the stimulus. As soon as it gets the reward for the selected action, the pleasure feelings originated which force the agent to perform the action in a more rapid way. This behavior can be clearly seen in Fig. 2, the preparation of action get higher as soon as the reward has been anticipated.

Moreover, the Fig. 3, shows the learning for the connections between feeling and the preparation of action. It can be seen that first action has been learned quite earlier than the other two actions because the agent learning process has been ignited by the release of dopamine through reward (see Fig. 4). Lastly, the continuous use of the reward increase expectation and which lead to slow learning or even make learning to asymptote. This behavior is implemented through control state which gets activated when the value of rewards and the expectation gets higher, the red line from control to feeling state of action is suppressed and leaning gets stops.

5 Mathematical Analysis for Hebbian Learning

Mathematical analysis of certain properties (equilibria, monotonicity an limit cycle) of a model can help verifying the dynamics of a model. Equilibrium is the property where for some values for the state no change occurs and how this may depends on the values of the parameters of the model and/or the initial values of the states [14]. For Hebbian adaption it can also be analyzed from the difference or differential equation.

Here the focus is on ω from the Eq. 8 it can be analyzed when the following cases occurs:

$$\mathbf{d}\omega(\mathrm{t})/\mathrm{d}t > 0 \Leftrightarrow \eta\ \mathrm{fs}_{\mathrm{a}i}(\mathrm{t})\mathrm{ps}_{\mathrm{a}i}(\mathrm{t})(1-\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}(\mathrm{t})) - \zeta\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}(\mathrm{t})] > 0\,(\text{Increasing}) \tag{9}$$

$$\mathbf{d}\omega(\mathrm{t})/\mathrm{d}t = 0 \Leftrightarrow \eta\ \mathrm{fs}_{\mathrm{a}i}(\mathrm{t})\mathrm{ps}_{\mathrm{a}i}(\mathrm{t})(1-\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}(\mathrm{t})) - \zeta\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}(\mathrm{t})] = 0\,(\text{stationary}) \tag{10}$$

$$\mathbf{d}\omega(\mathrm{t})/\mathrm{d}t < 0 \Leftrightarrow \eta\ \mathrm{fs}_{\mathrm{a}i}(\mathrm{t})\mathrm{ps}_{\mathrm{a}i}(\mathrm{t})(1-\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}(\mathrm{t})) - \zeta\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}(\mathrm{t})] < 0\,(\text{Decreasing}) \tag{11}$$

As we are interested in stationary points the Eq. 10 can be further reduced and t is left out for convenience: $[\eta\ \mathrm{fs}_{\mathrm{a}i}, \mathrm{ps}_{\mathrm{a}i}(1-\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}) - \zeta\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}] = 0$

$$\Leftrightarrow \omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)} = \eta\ \mathrm{fs}_{\mathrm{a}i},\ \mathrm{ps}_{\mathrm{a}i}/\zeta + \eta\ \mathrm{fs}_{\mathrm{a}i,}\mathrm{ps}_{\mathrm{a}i}$$

$$\Leftrightarrow \omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)} = 1/1 + \zeta/\left(\eta\ \mathrm{fs}_{\mathrm{a}i,}\mathrm{ps}_{\mathrm{a}i}\right)(\text{when both states value} > 0) \tag{12}$$

$$\Leftrightarrow \eta\ \mathrm{fs}_{\mathrm{a}i},\ \mathrm{ps}_{\mathrm{a}i}(1-\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}) - \zeta\omega_{\mathrm{fs}(\mathrm{a}i),\mathrm{ps}(\mathrm{a}i)}] = 0(\text{when both states value and } \zeta = 0) \tag{13}$$

The Table 4, shows the equilibrium values by Eq. 12, the deviation between the values on left and right side of equation are less than 0.03. It can be concluded that the analysis of equilibria gives an evidence that the model was correctly implemented.

Table 4. Equilibrium value confirmation.

Time step	Connection value $\omega_{fs(ai),ps(ai)}$	State Values	Speed factor η	Extinction ζ	Equilibrium by Eq. 12
3183	$\omega_{fs(a1),ps(a1)} = 0.8299$	0.4634, 0.9999	0.2	0.095	0.8196
3127	$\omega_{fs(a2),ps(a2)} = 0.8321$	0.4725, 0.9966	0.2	0.095	0.8201
3193	$\omega_{fs(a2),ps(a2)} = 0.8089$	0.4047, 0.9966	0.2	0.095	0.8301

6 Conclusion

The model presented in this paper is a neurologically inspired computational model for reward-based learning by involving a number of internal and external factors. The focus of this paper is to formalise the dynamics and interaction of internal states which are involved in decision making and associative learning. The model based on internal prediction in combination with associated feelings for valuation of the available actions.

The simulation results suggest that this model is capable of learning of making action choices on the one hand and through levels of expectation in relation to various types of actions on the other hand. The proposed computational model for making reward-based learning can be used to develop motivation monitoring intelligent systems that can help and support persons with motivation toward achieving his/her goals and targets. In future work, the model will be extended with motivation regulation strategies, and further focus will be on the social and environmental factors.

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